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Forecasting the Prices of Credit Default Swaps of Greece by a Neuro-fuzzy Technique

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Forecasting the Prices of Credit Default Swaps of Greece by a Neuro-fuzzy Technique

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Abstract: Derivative products are contracts, the value of which results from the underlying primary financial product which may be a stock, an interest rate, a foreign currency, a bond, a regulated market indicator or a commodity (for example sugar, gold, oil and others). One of the most widespread financial derivatives is the swaps, which include Credit Default Swaps (CDSs). This paper presents a model that forecasts the daily prices of credit default swaps by the development of an Adaptive Neural Network with Fuzzy Inference system (ANFIS), using data that concern daily prices of the Greek credit default swaps. The results indicate that fuzzy neural networks could be an efficient system that is easy to apply in order to accurately forecast the prices of credit default swaps of Greece.

Keywords: neuro-fuzzy forecasting, ANFIS, neural network, credit default swaps forecasting

1. Introduction

Derivative products are very popular due to their ability to offset financial risks. Generally, swaps are contracts that cover agreements between two parts, as far as exchange of inflows or outflows in the future with predetermined terms is concerned. Swaps are created and moved mainly over-the-counter and they are not standardized products, but their features are formed by the counterparties so that they cover the counterparties' needs exactly, which means that swaps are cleared on the grounds that one counterparty collects money and the other one pays the contract price. The most widespread categories of swaps are the currency swaps and the interest rate swaps. More specifically, credit default swaps are the most popular types of credit derivatives (Young et.al, 2010) and the most frequently negotiated credit derivatives, capturing almost 45% of market share. Moreover, they are considered by many, maybe the most important and successful financial innovation of the last decade (Norden and Wagner, 2008). According to the version of a report about financial stability conducted by the Bank of Greece, credit default swaps are derivative products that are associated with the credit risk of specific underlying assets (usually bonds and loans) and operate as a kind of ensuring the buyer of such a product, as the seller undertakes, after taking a premium, to compensate the buyer in the event that the publisher of the underlying asset defaults. These contracts are a tool for the transfer of the credit risk of a reference asset from one investor to another without transferring the ownership of this asset. Furthermore, a credit default swap is a bilateral derivative contract over one or more reference assets, in which the protection buyer pays a fee that is called a premium, during the lifetime of the contract in return for the payment of a credit event by the protection seller, and this payment follows after a credit event of the reference entities. According to Jarrow (2010), the reference entity may be a company or a government, but it could also be a Collateralized Debt Obligations (CDO) bond, which is called an Asset Backed Security (ABS). In most cases, the protection buyer makes periodic payments to the protection seller, which is typically expressed in terms of the credit default swap’s spread, the annualized percentage of the nominal amount of a transaction. In case that no predetermined credit event takes place during the lifetime of the transaction, the protection seller receives the periodic payments as compensation for the fact that he assumes the credit risk concerning the reference entity or the reference obligation. In contrast to the above, in case that any of the credit events takes place during the lifetime of the transaction, the protection buyer will receive a payment for this credit event which will depend on whether the terms of the specific credit default swap refer to physical settlement, cash settlement or fixed amount settlement.

According to the researches, the neural networks have been accused that they are not being able to recognize the degree to which an input can influence the output of the model and that the “black box” syndrome that characterizes them restricts their applicability (Saphiro, 2002). Also, another limitation of the neural network is that it should be of feed forward type and due to this restriction; the adaptive network’s applications are immediate and immense in various areas. Fuzzy logic, instead, handles with imprecise information and linguistic concepts, develops the approximate reasoning in order to perform non-linear mappings between inputs and outputs, but it is not capable of self learning. This study proposes the use of a hybrid intelligent system called ANFIS for predicting the prices of credit default swaps of Greek government bonds, which combines the learning capabilities of a neural network and the reasoning capabilities of fuzzy logic in order to achieve improved prediction capabilities, avoiding rule matching time of an inference engine in the traditional fuzzy logic system (Hornik, 1991).

The novelty of this study is that for first time an ANFIS model is applied to forecast the CDs daily prices. The rest of the paper is organized as follows: Section 2 reviews related research and Section 3 discusses the proposed methodology. Section 4 outlines the data and reports the empirical findings, while Section 5 includes the conclusions and some further discussions about the future research in this sector.

2. Literature review and related work

As far as forecasting the prices of credit default swaps of Greece with the development and use of the ANFIS system, artificial neural networks, fuzzy logic, stochastic models or other methods and even integration of two or more methods is concerned, there is limited relevant research and literature. These studies are the following: Shaban et.al, (2010) have forecasted the prices of credit default swaps using artificial neural networks. Gündüz and Uhrig-Homburg, (2011) have predicted credit default swap prices with financial and pure data-driven approaches. Apart from this literature, most important related studies that have addressed the problem of financial time series prediction are cited and are the following: Pesando, (1981) has forecasted interest rates as well as Rudin, (1988), Cargill and Meyer, (1983) have forecasted the term structure of interest rates and portfolio planning models, Allen and Hafer, (1984) have also forecasted the term structure of interest rates, Marwan, (1985) has forecasted capital flows and exchange rates of the foreign exchange market of Canada, Kolluri and Giannaros, (1987) have forecasted budget deficits and short-term real interest rate, Vinod and Basu, (1995) have forecasted consumption, income and real interest rates using alternative state space models, Gupta and Moazzami, (1991) have forecasted the recent interest rate behavior using the error-correction modeling approach, Fletcher and Gulley, (1996) have forecasted the real interest rate as well as Bidarkota, (1998) using univariate and multivariate models, Estrella and Mishkin, (1997) have forecasted the term structure of interest rates in Europe and the United States with implications for the European Central Bank, Ju et.al., (1997) have forecasted the interest rate using genetic-based fuzzy models as well as Kim and Noh, (1997) that used data mining tools and made a comparative analysis of Korea and the US, Blomberg and Hess, (1997) have forecasted the exchange rate, Byers and Nowman, (1998) have forecasted U.K. and U.S. interest rates using continuous time term structure models, Hu and Tsoukalas, (1999) have forecasted the EMS exchange rates using neural networks, Richards, (2000) has forecasted the fractal structure of exchange rates, Oh and Han, (2001) have forecasted interest rates using artificial neural networks, Ferreira, (2005) has forecasted the comovements of spot interest rates, Elger et.al., (2006) have forecasted various monetary aggregates using recent evidence for the United States, Atsalakis et.al., (2008) have forecasted federal funds effective rate using a neuro-fuzzy system, Blaskowitz and Herwartz, (2009) have forecasted the Euribor swap term structure using adaptive models, Dauwe and Moura, (2011) have forecasted the term structure of the Euro market using principal component analysis, Blaskowitz et.al., (2005) have forecasted the Fibor/Euribor swap term structure using an empirical approach, Pacelli et.al., (2011) have forecasted exchange rates using an artificial neural network model, Bianco et.al., (2008) have forecasted the Euro-Dollar exchange rate using economic fundamentals, Zhang and Hu, (1998) have forecasted the British Pound/US Dollar Exchange Rate using neural networks and Yu et.al., (2005) have forecasted foreign exchange rate using adaptive smoothing neural networks, Skiadas et.al., (2001) with the paper titled “Chaotic Aspects of a Generalized Rational Model and Application in Innovation Management” , Atsalakis et.al., (2007) with the paper titled “Probability of trend prediction of exchange rate by neuro-fuzzy techniques”, Maguire et.al., (1998) have forecasted a chaotic time series using a fuzzy neural network, Atsalakis et.al., (2008) have forecasted chaotic time series using a neural network, Farmer and Sidorowich, (1987) have forecasted chaotic time series using a forecasting technique, Szpiro, (1997) has forecasted chaotic time series using genetic algorithms, Studer and

Masulli, (1996) have forecasted chaotic time series using a neuro-fuzzy system, Palit and Popovic, (1999) have forecasted chaotic time series using neuro-fuzzy approach, Zhao and Yang, (2009) have used PSO-based single multiplicative neuron model for time series prediction, Fukunaga and Narihisa, (2001) have used efficient hybrid neural network for chaotic time series prediction, Abiyev, (2006) has forecasted time series using a fuzzy wavelet neural network model, Nie, (1994) has forecasted time series using a fuzzy-neural approach, Hassan et.al., (2006) have forecasted time series using HMM based fuzzy model, Assaad et.al., (2006) have forecasted chaotic time series using boosted recurrent neural networks, Gang et.al., (2008) have forecasted time series using a wavelet process neural network, Vairappan et.al., (2009) have forecasted time series using batch type local search-based adaptive neuro-fuzzy inference system (ANFIS) with self-feedbacks, Gao and Xiao, (2004) have forecasted chaotic time series using multiwavelet networks, Wan et.al., (2005) have forecasted chaotic time series using support vector machines for fuzzy rule-based modeling, Wong et.al., (2010) have forecasted time series using an adaptive neural network model, Wang et.al., (2005) have forecasted chaotic time series based on SVD matrix decomposition, Ardalani-Farsa and Zolfaghari, (2010) have forecasted chaotic time series with residual analysis method using hybrid Elman-NARX neural networks, Liu and Yao, (2009) have forecasted chaotic time series using least square support vector machine based on particle swarm optimization, Song et.al., (2010) have forecasted chaotic time series using neural networks, Wang and Gu, (2009) have forecasted chaotic time series based on neural network with Legendre polynomials, Chen et.al., (2007) have forecasted time series using an artificial neural networks based dynamic decision model, Pan et.al., (2009) have forecasted time series using a hybrid forecasting model and Ye, (2007) has forecasted chaotic time series using LS-SVM with simulated annealing algorithms and Atsalakis et.al., (2011) have forecasted the Euribor rate using the ANFIS system.

3. ANFIS architecture

The ANFIS model has been successfully applied to a variety of scientific areas such as energy, stock market, financial indexes, robotic applications and others. There are many papers that have used ANFIS models with high degree of accuracy in financial forecasting. Atsalakis and Valavanis, (2009), have developed an ANFIS controller that forecasts stock market short-term trends. Atsalakis et.al, (2011) presented a model that forecasts the trend of the stock prices using the Elliott Wave Theory and neuro-fuzzy systems. Atsalakis et.al., (2010) presented a time series model that forecasts wind energy production using neuro-fuzzy models and compares the results of the prediction to those when using traditional models.

This paper is dealing with the development of a forecasting system based on ANFIS, which differs from the traditional Artificial Neural Networks (ANN) in that it is not fully connected and not all the weights or nodal parameters are modifiable. The model uses a hybrid learning algorithm to identify the parameters for the Sugeno-type fuzzy inference systems. It applies a combination of the least-squares method and the back-propagation gradient descent method for training the Fuzzy Inference System (FIS) membership function parameters to emulate the given training data set. Specifically, a back-propagation algorithm is used to optimize the fuzzy sets of the premises and a least-squares procedure is applied to the linear coefficients in the consequent terms. In addition, it uses a testing data set for checking the model over fitting. ANFIS is a multilayer neural network-based fuzzy consisted of five layers, in which the training and predicted values are represented by the input and output nodes and the nodes functioning as membership functions (MFs) and rules are presented in the hidden layers. Its topology is shown in Figure 1. During the learning phase of ANFIS, the parameters of the membership functions are changing continuously in order to minimize the error function between the target output and the calculated values.

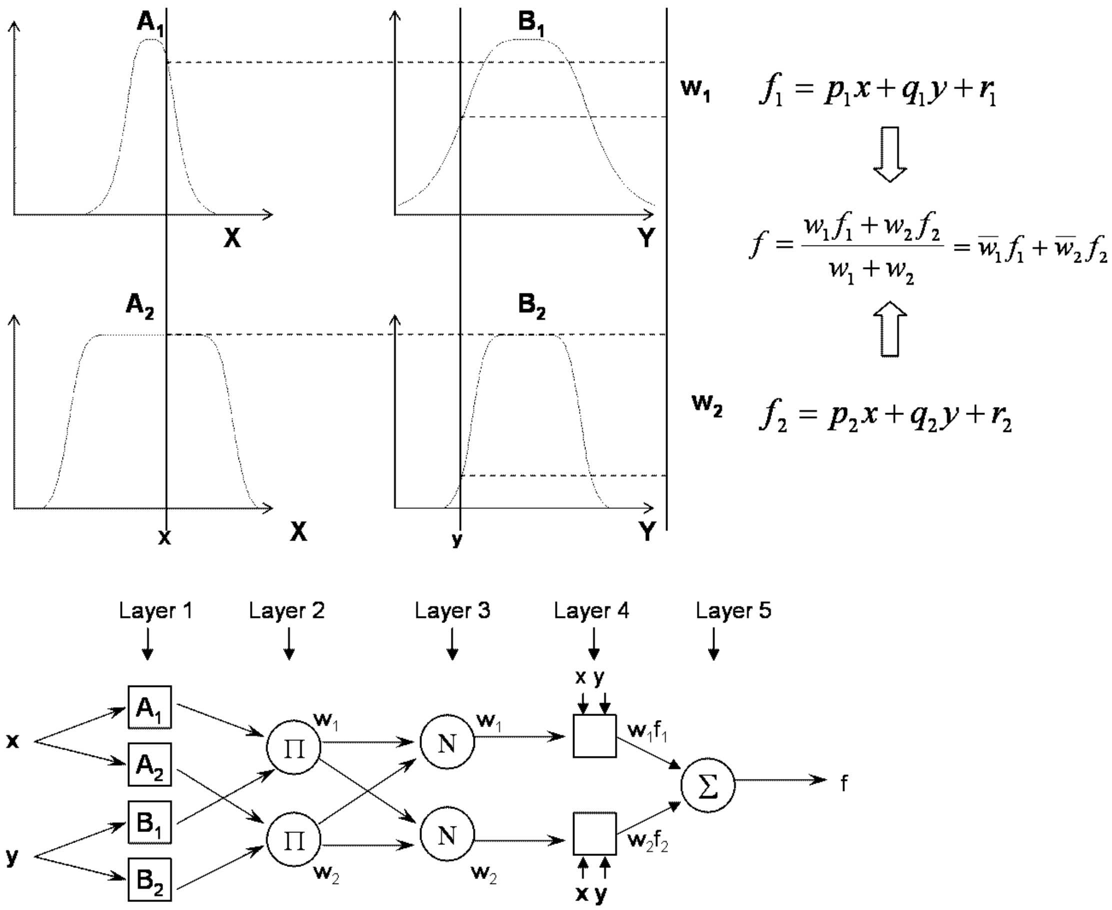

Figure 1. An illustration of the reasoning mechanism for a Sugeno-type model and the corresponding ANFIS architecture (Jang, 1997)

For simplicity, it is assumed that the examined fuzzy inference system has two inputs, x and y, and one output. For the first-order Sugeno fuzzy model, a typical fuzzy rule set in this model, with two fuzzy If-Then rules, has the following form (Jang, 1995):

Rule1: If x is A_1 and y is B_1 then $f_1 = p_1 \cdot x + q_1 \cdot y + r_1$ (1)

Rule2: If x is A_2 and y is B_2 then $f_2 = p_2 \cdot x + q_2 \cdot y + r_2$ (2)

This architecture develops an adaptive network that is functionally equivalent to a two inputs first-order Sugeno fuzzy model with four rules, where each input has two membership functions. The error measure to train the aforementioned ANFIS is defined as:

$$E = \sum_{k=1}^{n} (y_k - \hat{y}_k)^2 \qquad (3)$$

where y_k and $\hat{y}_k$ are the kth desired and estimated output, respectively, and n is the total number of pairs (inputs–outputs) of data in the training set. Due to its efficiency and transparency, ANFIS is outperforming other models.

4. Experimental data and performance of the model

The experimental data concerns a time series of daily prices of credit default swaps of Greece, ranging from March 2003 to June 2011, in total 2170 samples. The model forecasts the prices of credit default swaps one step ahead. The 2047 samples have been used as training data for training the model and the remaining 121 have been used as evaluation data to test the prediction performance of the resulting model. The structure of ANFIS consist one input and one output, which means that the forecasting system is used to predict the next day value of credit default swaps of Greece based on the previous values. The method of trial and error is used in order to decide the type and number of membership functions, the number of epochs and the step size that best describe the model and provide the lowest error. The optimal fuzzy inference is achieved after 1000 epochs with two membership functions of gauss shape and the step size set in 0.01. Figure 2 depicts the initial MFs of each input variable before the training of the model and figure 3 depicts the final MFs after the completion of the training process. The comparison between the initial and the final MFs of the input data indicates important differences and the model resulted in remarkable deviation between the initial and the final MFs.

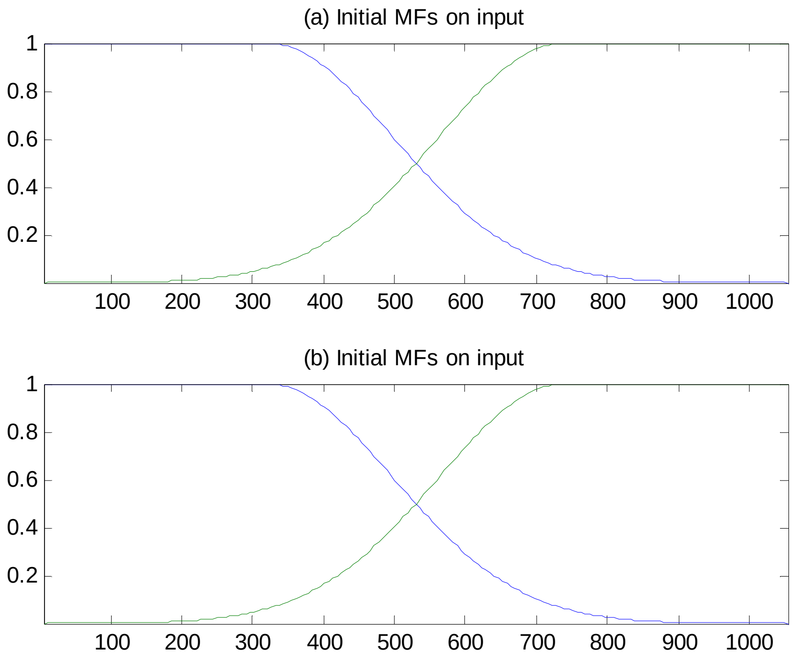

Figure 2. Form of Membership Functions before training

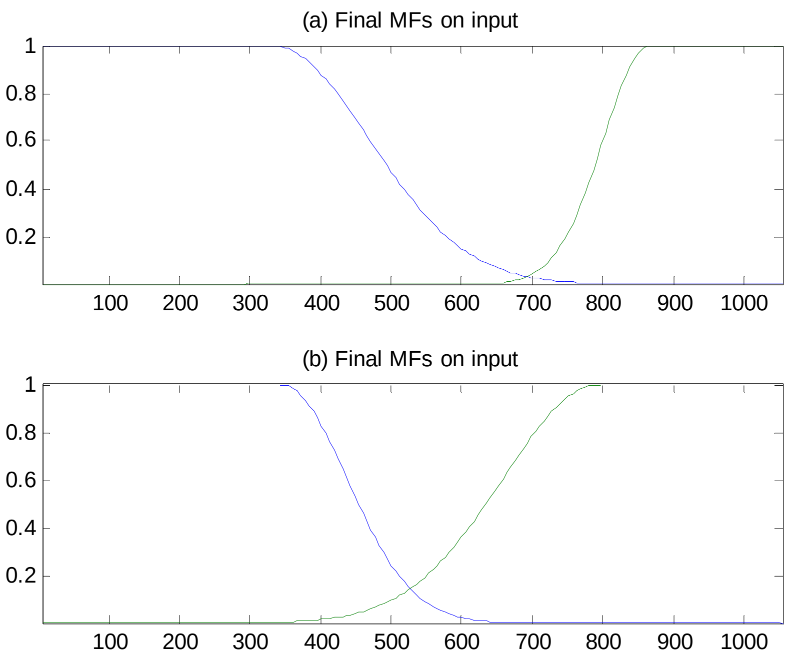

Figure 3. Form of Membership Functions after training

Moreover, figure 4 depicts the out of sample results produced by the Adaptive-Network-based Fuzzy Inference System (ANFIS). It can be seen that the actual values and the values from the ANFIS prediction are almost identical, which means that the model is performing very satisfactory.

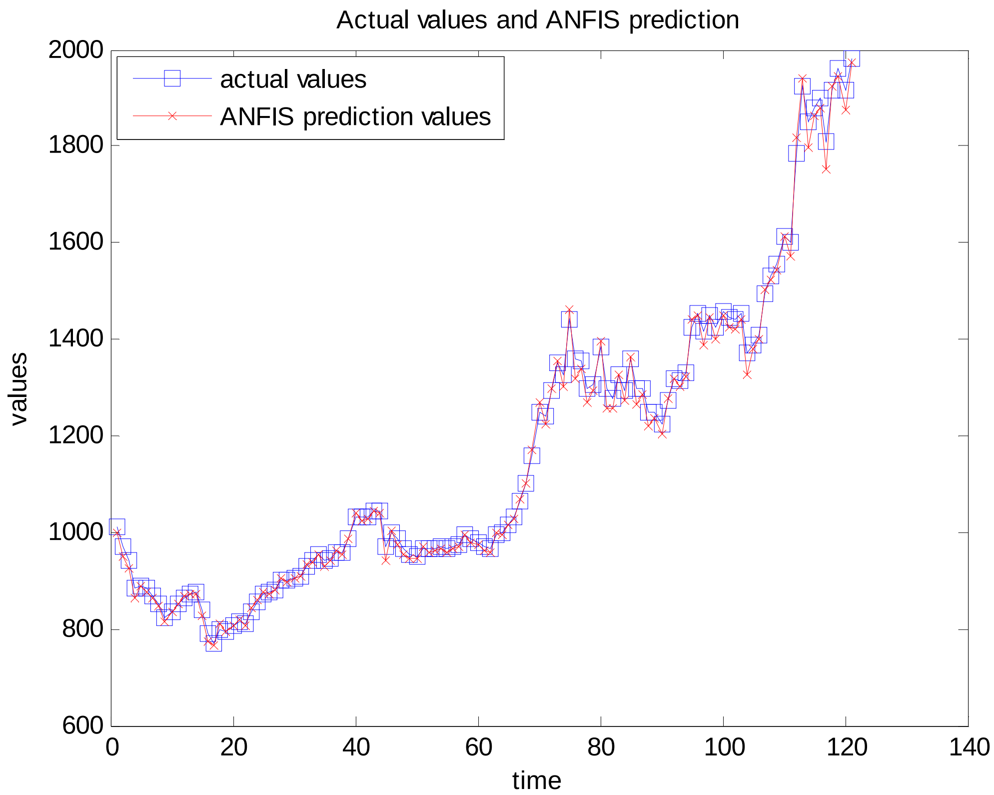

Figure 4. ANFIS out of sample forecasting results

Lastly, figure 5 shows the ANFIS error curves and the ANFIS step size curve.

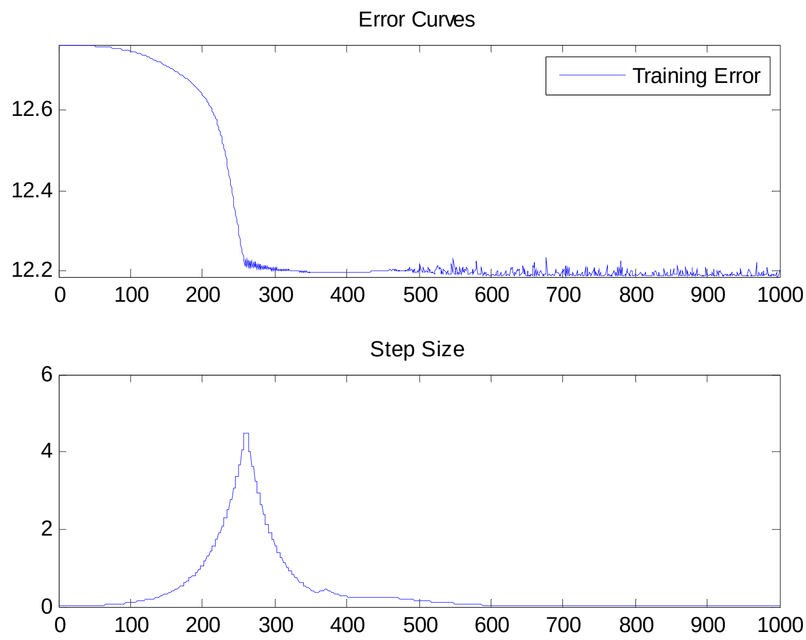

Figure 5. ANFIS error curves and ANFIS step size curve

The network applies 4 rules and there is one input and one output. Table 1 describes the type and values of the ANFIS parameters.

Table 1: ANFIS parameter types and their values used for training

ANFIS parameter type	**Value**
MF type	Gauss function
Number of MFs	2
Output MF	Linear
Number of Nodes	21
Number of linear parameters	12
Number of nonlinear parameters	16
Total number of parameters	28
Number of training data pairs	2047
Number of evaluating data pairs	121
Number of fuzzy rules	4

During the evaluation phase, the out of sample data is carried out and the output of the model is compared with the actual data of the next day. The performance of the model is examined using the main statistical errors of: Mean square error (MSE), Root mean square error (RMSE), Mean absolute error (MAE) and Mean absolute percentage error (MAPE). Table 2 summarizes the results of the statistical analysis.

Table 2: Statistical performance of the ANFIS model

	ANFIS
MSE	4.6568986
RMSE	0.0068241
MAE	0.0019778
MAPE	0.0000065

The results indicate that the forecasting performance of ANFIS is satisfactory and acceptable both in research and in practice.

5. Conclusion

This paper presents a Fuzzy Inference System for the prediction of daily prices of credit default swaps of Greece. The model is developed using Matlab software. The results of the prediction are satisfactory and encouraging. Fuzzy logic theory could predict well, as far as modeling on uncertain data is concerned. The use of ANFIS to predict the prices of credit default swaps of Greece have the following advantages:

a) ANFIS is simple to maintain and apply on forecast practically.

b) It combines the capabilities of fuzzy systems and neural networks.

c) Fuzzy rule based system incorporates the flexibility of human decision making by means of the use of fuzzy set theory and makes use of fuzzy linguistic terms described by MFs.

d) It requires fewer and simpler trials and errors for optimization of their architecture.

e) It is nonlinear and capable of adapting and learning fast from numerical and linguistic knowledge.

f) ANFIS is a model-free, easy to implement approach. In contrast to traditional time series methods, little training is needed to calculate predictions with ANFIS. It implements a single-fitting procedure to nonlinear situations, without the need of establishing a formal model for the problem being resolved. Thus, no a priori information is required to determine the empirical relationship between explanatory and predicted variables and the method suitability is always tested a posteriori.

e) The transparent rule structure of ANFIS allows the researcher to extract information about the empirical relationship between the inputs and the outputs over time and to provide concise explanations.

In conclusion, these forecasting results can provide useful information and guidance for financial and market analysts. Yet, further research is recommended in order to improve the forecast results. Some suggestions for further research could be the use of more data concerning the years before 2003 in order to forecast the daily prices of credit default swaps, the use of more inputs in order to take the output which is the forecast of these prices or the use of data concerning the daily prices of credit default swaps of other countries in order to compare the results of the prediction for each country.

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